

# Data and Statistical Analyses: Tips and Tricks

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# I Hate p-Values!



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# I Hate p-Values



Karl Pearson

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# I Hate p-Values



Karl Pearson

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George Udny Yule

# I Hate p-Values



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George Udny Yule



William Gossett (Student)

# I Hate p-Values



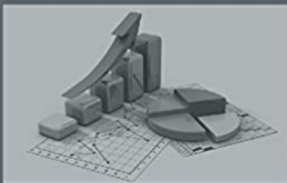
Ronald Aylmer Fisher



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# What's the Story with $p < 0.05$ ?

## Statistical Methods for Research Workers



**R.A. Fisher**

# What's the Story with $p < 0.05$ ?

F - Distribution ( $\alpha = 0.01$  in the Right Tail)

| Denominator Degrees of Freedom | df <sub>2</sub> | Numerator Degrees of Freedom |        |        |        |        |        |        |        |   |
|--------------------------------|-----------------|------------------------------|--------|--------|--------|--------|--------|--------|--------|---|
|                                |                 | 1                            | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9 |
| 1                              | 4052.2          | 4999.5                       | 5403.4 | 5624.6 | 5763.6 | 5859.0 | 5928.4 | 5981.1 | 6022.5 |   |
| 2                              | 98.503          | 99.000                       | 99.166 | 99.249 | 99.299 | 99.333 | 99.356 | 99.374 | 99.388 |   |
| 3                              | 34.116          | 30.817                       | 29.457 | 28.710 | 28.237 | 27.911 | 27.672 | 27.489 | 27.345 |   |
| 4                              | 21.198          | 18.000                       | 16.694 | 15.977 | 15.522 | 15.207 | 14.976 | 14.799 | 14.659 |   |
| 5                              | 16.258          | 13.274                       | 12.060 | 11.392 | 10.967 | 10.672 | 10.456 | 10.289 | 10.158 |   |
| 6                              | 13.745          | 10.925                       | 9.7795 | 9.1483 | 8.7459 | 8.4661 | 8.2600 | 8.1017 | 7.9761 |   |
| 7                              | 12.246          | 9.5466                       | 8.4513 | 7.8466 | 7.4604 | 7.1914 | 6.9928 | 6.8400 | 6.7188 |   |
| 8                              | 11.259          | 8.6491                       | 7.5910 | 7.0061 | 6.6318 | 6.3707 | 6.1776 | 6.0289 | 5.9106 |   |
| 9                              | 10.561          | 8.0215                       | 6.9919 | 6.4221 | 6.0569 | 5.8018 | 5.6129 | 5.4671 | 5.3511 |   |
| 10                             | 10.044          | 7.5594                       | 6.5523 | 5.9943 | 5.6363 | 5.3858 | 5.2001 | 5.0567 | 4.9424 |   |
| 11                             | 9.6460          | 7.2057                       | 6.2167 | 5.6683 | 5.3160 | 5.0692 | 4.8861 | 4.7445 | 4.6315 |   |
| 12                             | 9.3302          | 6.9266                       | 5.9525 | 5.4120 | 5.0643 | 4.8206 | 4.6395 | 4.4994 | 4.3875 |   |
| 13                             | 9.0738          | 6.7010                       | 5.7394 | 5.2053 | 4.8616 | 4.6204 | 4.4410 | 4.3021 | 4.1911 |   |
| 14                             | 8.8616          | 6.5149                       | 5.5639 | 5.0354 | 4.6950 | 4.4558 | 4.2779 | 4.1399 | 4.0297 |   |
| 15                             | 8.6831          | 6.3589                       | 5.4170 | 4.8932 | 4.5556 | 4.3183 | 4.1415 | 4.0045 | 3.8948 |   |
| 16                             | 8.5310          | 6.2262                       | 5.2922 | 4.7726 | 4.4374 | 4.2016 | 4.0259 | 3.8896 | 3.7804 |   |
| 17                             | 8.3997          | 6.1121                       | 5.1850 | 4.6690 | 4.3359 | 4.1015 | 3.9267 | 3.7910 | 3.6822 |   |
| 18                             | 8.2854          | 6.0129                       | 5.0919 | 4.5790 | 4.2479 | 4.0146 | 3.8406 | 3.7054 | 3.5971 |   |
| 19                             | 8.1849          | 5.9259                       | 5.0103 | 4.5003 | 4.1708 | 3.9386 | 3.7653 | 3.6305 | 3.5225 |   |
| 20                             | 8.0960          | 5.8489                       | 4.9382 | 4.4307 | 4.1027 | 3.8714 | 3.6987 | 3.5644 | 3.4567 |   |
| 21                             | 8.0166          | 5.7804                       | 4.8740 | 4.3688 | 4.0421 | 3.8117 | 3.6396 | 3.5056 | 3.3981 |   |
| 22                             | 7.9454          | 5.7190                       | 4.8166 | 4.3134 | 3.9880 | 3.7583 | 3.5867 | 3.4530 | 3.3458 |   |
| 23                             | 7.8811          | 5.6637                       | 4.7649 | 4.2636 | 3.9392 | 3.7102 | 3.5390 | 3.4057 | 3.2986 |   |
| 24                             | 7.8229          | 5.6136                       | 4.7181 | 4.2184 | 3.8951 | 3.6667 | 3.4959 | 3.3629 | 3.2560 |   |
| 25                             | 7.7698          | 5.5680                       | 4.6755 | 4.1774 | 3.8550 | 3.6272 | 3.4568 | 3.3239 | 3.2172 |   |
| 26                             | 7.7213          | 5.5263                       | 4.6366 | 4.1400 | 3.8183 | 3.5911 | 3.4210 | 3.2884 | 3.1818 |   |
| 27                             | 7.6767          | 5.4881                       | 4.6009 | 4.1056 | 3.7848 | 3.5580 | 3.3882 | 3.2558 | 3.1494 |   |
| 28                             | 7.6356          | 5.4529                       | 4.5681 | 4.0740 | 3.7539 | 3.5276 | 3.3581 | 3.2259 | 3.1195 |   |
| 29                             | 7.5977          | 5.4204                       | 4.5378 | 4.0449 | 3.7254 | 3.4995 | 3.3303 | 3.1982 | 3.0920 |   |
| 30                             | 7.5625          | 5.3903                       | 4.5097 | 4.0179 | 3.6990 | 3.4735 | 3.3045 | 3.1726 | 3.0665 |   |
| 40                             | 7.3141          | 5.1785                       | 4.3126 | 3.8283 | 3.5138 | 3.2910 | 3.1238 | 2.9930 | 2.8876 |   |
| 60                             | 7.0771          | 4.9774                       | 4.1259 | 3.6490 | 3.3389 | 3.1187 | 2.9530 | 2.8233 | 2.7185 |   |
| 120                            | 6.8509          | 4.7865                       | 3.9491 | 3.4795 | 3.1735 | 2.9559 | 2.7918 | 2.6629 | 2.5586 |   |
| $\infty$                       | 6.6349          | 4.6052                       | 3.7816 | 3.3192 | 3.0173 | 2.8020 | 2.6393 | 2.5113 | 2.4073 |   |



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# Multiple Comparisons

- If you report many p-values, you increase your *family-wise* error rate
- How many tests did you run, and how many did you report?
- Adjust. . .
  - Bonferroni
  - Tukey
  - Stepdown
- These will reduce your FWER, but impact your power. You could not adjust. . .
  - Say how many tests you ran
  - Don't adjust the tests
  - Let the reader decide



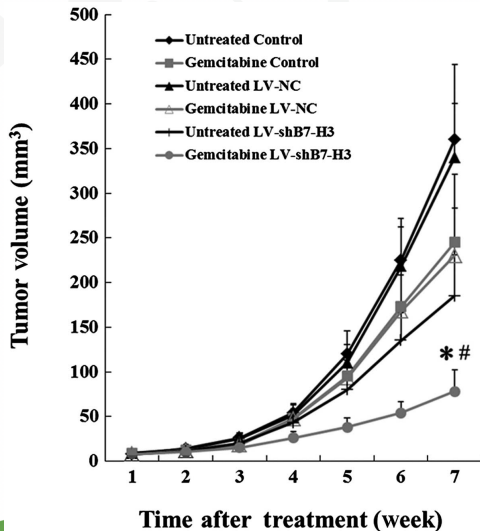
# Repeated Measures Are Your Friends



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# What Is The Point Here?

- How many animals are in each curve?
- How many animals are being lost to ethical sacrifice?
- Are we just interested in the comparison at one time point?
- Why are the confidence intervals getting bigger?

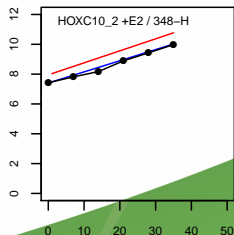
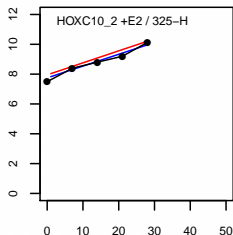
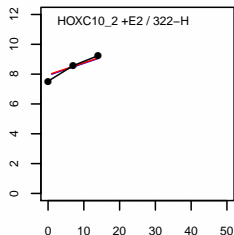
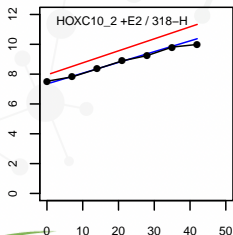
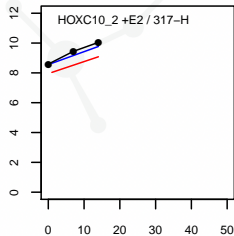
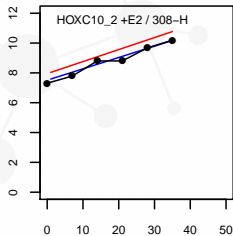
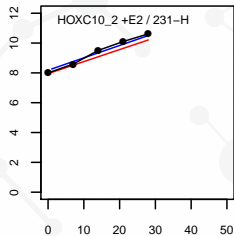
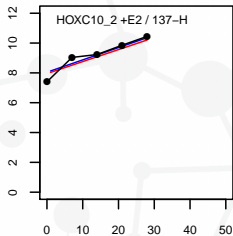


# A Better Idea

- Linearize exponential growth with the log transform
- Fit a line to each animal
- The slope of the line is the tumor growth rate
- Compare growth rates between treatment groups
- No bias induced by ethical sacrifice
- Increase statistical power
- Use *all* the data!



# Fit The Animals, Average the Fits



# Repeated Measures in Xenograft Experiments

- Random slopes and intercepts (mixed effects) model does the analysis above in one model

$$\log_2(V_{ij}(t)) = \alpha_i + \beta_i t + a_{ij} + b_{ij} t + e_{ijt}$$

Pop.

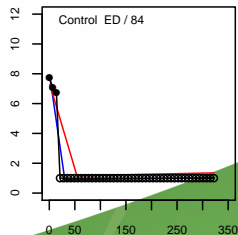
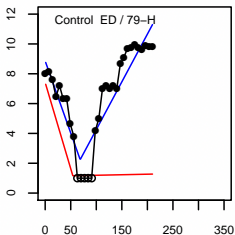
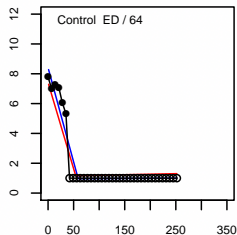
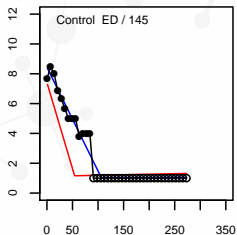
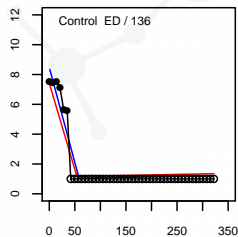
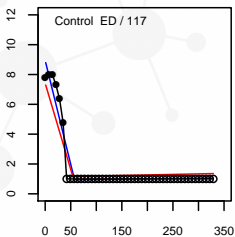
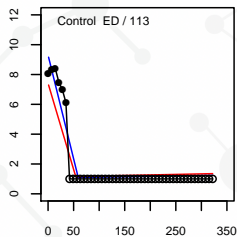
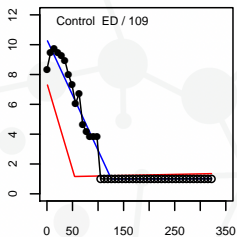
Animal

Noise

- Compare  $\beta$ s using Wald-type tests
- Software
  - SAS Proc Mixed
  - R function lmer() in package lmerTest
  - Python function mixedlm() in package statsmodels



# “Broken Stick” Model



**I Agree With Leslie**

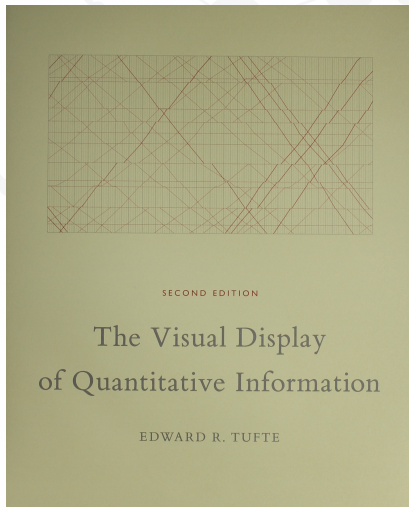


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# A Good Book

Not to be confused with *The Good Book*



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# What Is All This?



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# What Is *Data Science*?

- Term was coined by Bell Labs Statistician Bill Cleveland in 1991
- He used it to compare (favorably) a proposed course of training to mine:
  - Explicit training in computer programming
  - Training in data wrangling
  - Emphasis on collaborative research
- Some data science programs will have more emphasis on advanced applied computing (e.g., how to use a Hadoop Cluster) and machine learning techniques



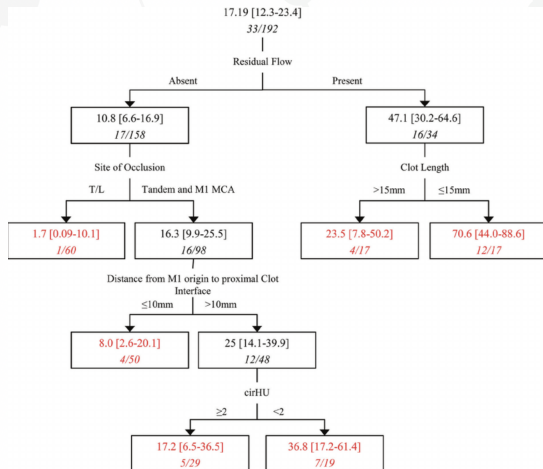
# What Is *Machine Learning*?

- Machine learning emphasizes Predictive Modeling, not inference (no p-values!)
- It includes many traditional statistical methods: regression, logistic regression, principal components, regularized regression
- It also includes “black box” predictive modeling methods that many statisticians know about, too: random forests, neural nets, ensemble modeling, support vector machines
- These methods can offer excellent predictive performance in cases of significant nonlinearity or very many predictors



# What Is *Random Forests*?

- It's souped up Recursive Partitioning  $\Rightarrow$
- Regression or Classification
- Recursive Partitioning has a reputation for over-fitting and sensitivity to small permutations in the data
- So, Leo Breiman fixed it



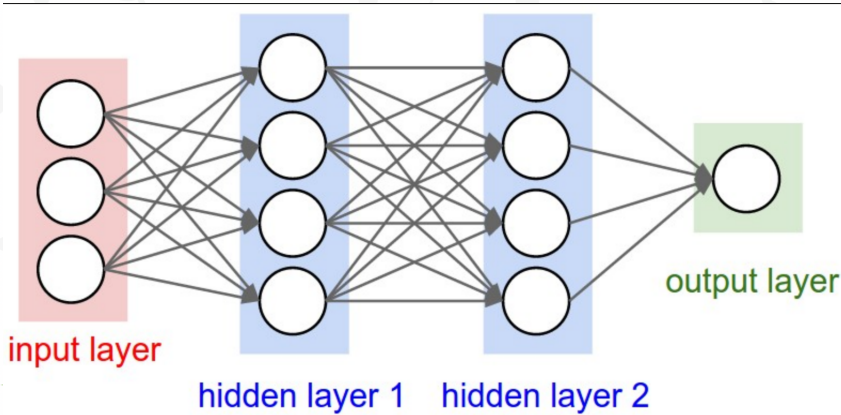
# What Is *Random Forests*?

- Do the following many (>tens of thousands of) times:
  - Take a bootstrap sample (with replacement) of the inputs and outputs in the training set
  - Take a random sample of the inputs ( $\sqrt{p}$ )
  - Fit the bootstrap sample inputs to the outputs using the random sample of the inputs
- Average the predictions of all those trees
- It works better. You can demonstrate it.



# What Is A *Neural Net*?

- It's a bunch of logistic regressions that feed into each other to ultimately produce a prediction



# What Is A *Neural Net*?

- Estimation of the models' parameters are done by *backpropagation*
- The estimation can be time consuming, but the resulting predictions can be made really fast
- There are implementations in R, Python, SAS and Matlab (and elsewhere, I'm sure)





# What Is *Deep Learning*?

- A neural net with more layers



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# What Is *Deep Learning*?

- A neural net with more layers
- It's getting deep in here. . .



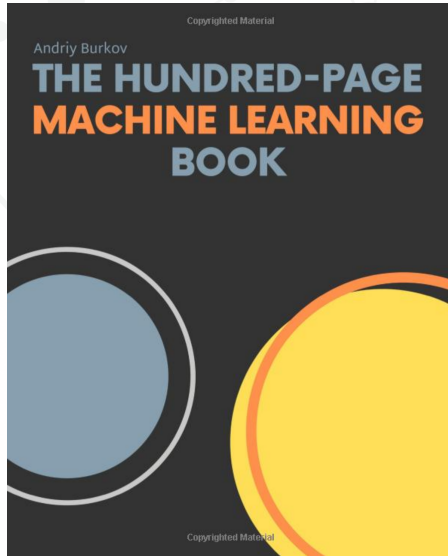
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# What Is An *Ensemble Model*?

- Run all the methods above to build predictive models
- Average them



# Another Good Book



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# What Is *Artificial Intelligence*?



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# What Is *Artificial Intelligence*?

Who the ■■■ knows?



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# Optimal Dichotimization



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# There Is An Optimal Cutpoint. Just Sayin'

## Expected Cost of a Decision

- Assign a unit to Population 1 or 2 based on a continuous random variable  $x$
- The cost of correct classification is 0
- $C_1 > 0$  is the cost of assigning a member of Population 1 to Population 2
- $C_2 > 0$  is the cost of assigning a member of Population 2 to Population 1
- It is also possible to generalize to the case where there is a non-zero cost of a correct decision
- $\pi$  is the prevalence of population 1 in the mixture
- Assume WLOG that the rule is: Assign member to Population 1 if  $x \leq c$



# Optimal Cutpoint

Minimize the Expected Cost

- The expected cost of this rule is:

$$\begin{aligned} E(c) &= \pi C_1 \int_{-\infty}^c f_1(x) dx + (1 - \pi) C_2 \int_c^{\infty} f_2(x) dx \\ &= \pi C_1 F_1(c) + (1 - \pi) C_2 (1 - F_2(c)) \end{aligned}$$

- To find the optimal value of  $c$ , set

$$\frac{d}{dc} E(c) = 0$$

# Optimal Cutpoint

Minimize the Expected Cost

- Then,

$$\begin{aligned}\frac{d}{dc}E(c) &= \pi C_1 f_1(c) - (1 - \pi) C_2 f_2(c) = 0 \Rightarrow \\ \pi C_1 f_1(c) &= (1 - \pi) C_2 f_2(c) \Rightarrow \\ \frac{\pi C_1}{(1 - \pi) C_2} &= \frac{f_2(c)}{f_1(c)}\end{aligned}$$

- This is the *Bayes minimum risk decision rule*



# Optimal Cutpoint

- Need  $\pi$ ,  $C_1$ ,  $C_2$ ,  $f_1$  and  $f_2$
- $f_1$  and  $f_2$  can be estimated from a sample
- $\pi$  is the prevalence in the population, not in the sample
- It's hard to come to a consensus on  $C_1$  and  $C_2$ ,
- Especially when one of the costs involves death



# What is Bayesian Statistics, Anyway?



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# Why Consider Bayesian Methods?

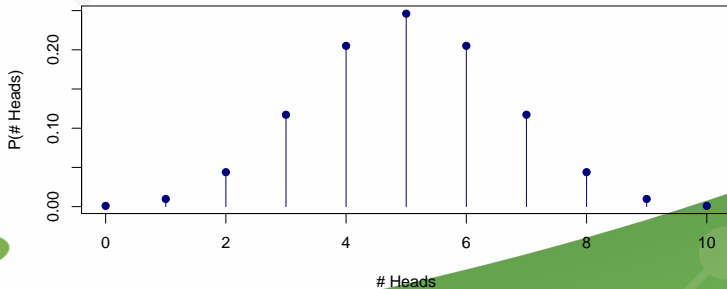
- Explicitly incorporate information outside the experiment into the data analysis
- Great flexibility in probability models
- Allow multiple looks at the data without penalty for multiple tests
- Monitoring clinical trials
- Model-based Phase I designs
- Response- and biomarker-adaptive clinical trials



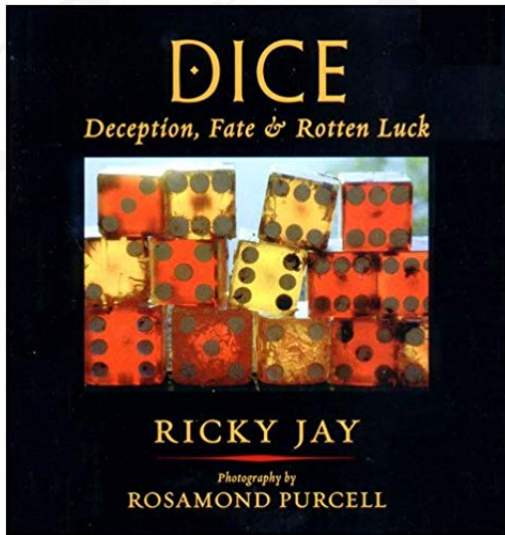
# The Frequentist Model of the Universe

- Repeated sampling of a random variable,  $\{X_1, X_2, X_3 \dots\}$  is described by a *probability distribution function*, indexed by *parameters*, e.g.,  $\mu, \sigma, \pi \dots$
- These parameters are *unobservable* and *fixed*
- Example: number of heads in  $n = 10$  coin tosses, where  $\pi = 1/2$ :

$$P(x \text{ heads in } n \text{ tosses} \mid \pi) = \binom{x}{n} \pi^x (1 - \pi)^{n-x}$$



# Yet Another



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# The Bayesian Model of the Universe

- Repeated sampling of a random variable,  $\{X_1, X_2, X_3 \dots\}$  is described by a *probability distribution function*, indexed by *parameters*, e.g.,  $\mu, \sigma, \pi \dots$
- These parameters are *unobservable* and *random*
- The parameters, being random variables themselves, have a probability distribution function themselves, which is called a *prior distribution*
- Example: number of heads in ten coin tosses:

$$P(x \text{ heads in } n \text{ tosses} | \pi) = \binom{x}{n} \pi^x (1 - \pi)^{n-x}$$
$$\pi \sim \text{Beta}(\alpha, \beta)$$

- $\alpha$  and  $\beta$  are called the *prior parameters* or *metaparameters*. They are set by the analyst.



# The Bayesian Model of the Universe

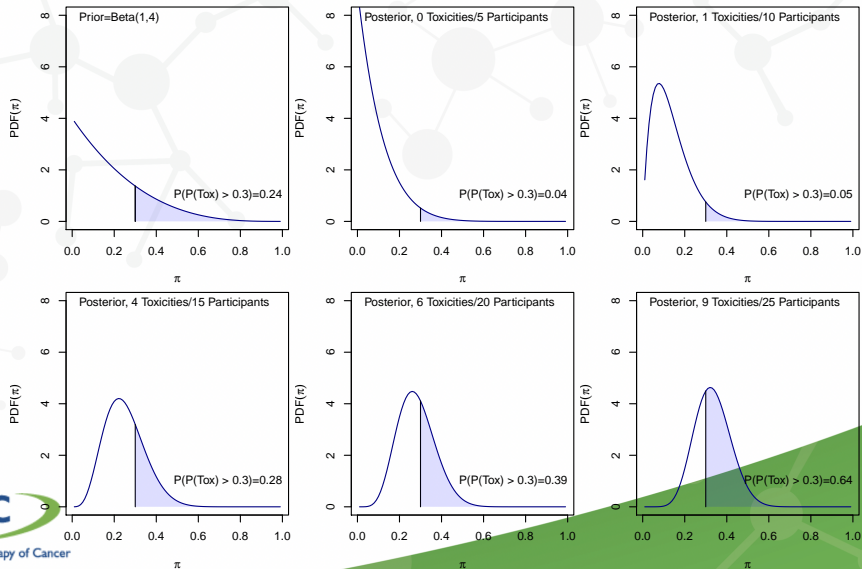
- Posterior  $\leftarrow$  Prior + Data
- The endpoint of a Bayesian analysis is a statement about the posterior distribution function (i.e., *after* the data have been observed) of the parameters of the probability function of the data
  - Frequentist: “A 95% confidence interval for  $\pi$  is (0.25, 0.45)”
  - Bayesian: “There is a 95% probability that  $\pi$  is between 0.25 and 0.45”
- Note that these are *not* the same
- The Bayesian model is convenient in continuous (or frequent) monitoring of clinical trials because hypothesis testing is not involved, so there is no inflation of the Type I error from multiple testing



## Example: Toxicity Monitoring

- “Accrual will be halted and the trial will be reevaluated if  $P(P(\text{Toxicity}) > 0.3) > 0.6$ ”
- We have a belief, not very strong, that the probability of toxicity,  $\pi$ , is around 0.2, so we choose a Beta(1,4) prior, which has the weight of  $1 + 4 = 5$  observations.

# Example: Toxicity Monitoring



# Bayesian Statistics in Medical Device Trials

- FDA defines a medical *device* as any product that does not achieve its purposes by chemical action or metabolization
- Many types of devices:

|                      |                  |                |
|----------------------|------------------|----------------|
| Contact lenses       | Breast implants  | MRI machines   |
| Surgical instruments | Hip replacements | Thermometers   |
| Artificial hearts    | Hearing aids     | Latex gloves   |
| Surgical stents      | Diagnostic tests | Defibrillators |

- Many (1,000s) small manufacturers
- Average life length of a device is two years
- Registration system for medical devices differs from that of drugs



# Bayesian Statistics in Medical Device Trials

- There are three classes of medical devices:
  - Class 1: Low risk, requiring only general controls (examples: adhesive bandage, sunglasses)
  - Class 2: Moderate risk, requiring general controls and special controls (examples: syringe, surgical mask, powered wheelchair)
  - Class 3: High risk, requiring general controls and pre-marketing approval (examples: heart valves, implantable neuromuscular stimulator)



# Bayesian Statistics in Medical Device Trials

- General controls:
  - Adulteration and misbranding
  - Quality systems
  - Labeling
  - Medical device reporting
  - Electronic Establishment Registration
  - Electronic Device Listing
  - Premarket Notification [510(k)]



# Bayesian Statistics in Medical Device Trials

- Special controls:
  - Guidelines (e.g., Glove Manual)
  - Mandatory Performance Standard
  - Recommendations or Other Actions
  - Special Labeling, specified in detail in 21 CFR 882



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# Bayesian Statistics in Medical Device Trials

- Pre-marketing approval:
  - Requires negotiation with FDA
  - Standards differ depending on the similarity of the new devices to existing devices already marketed
  - May or may not require a clinical trial





# Bayesian Statistics in Medical Device Trials

- Much prior information on similar devices
- For registration trials, FDA requires data-derived priors
- FDA negotiates with sponsor before registration trial on what constitutes valid prior data
- Prior data can be proprietary or publicly available
- Simulations are used to demonstrate operating characteristics
- Required sample sizes can be significantly decreased
- Sometimes use formal economic risk/benefit analysis



# Bayesian Medical Device Trial Example

- TherOx Downstream Aqueous Oxygen System
- Device used to deliver superoxygenated blood to patient's heart after MI
- FDA agreed to single randomized, controlled pivotal trial, AMIHOT I <sup>1</sup>



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<sup>1</sup>No, I did not make this up.

# AMIHOT I

- 289 patients from 23 centers, randomized 1:1
- Trial designed for noninferiority of safety endpoint (death, stroke, etc.)
- Trial designed for superiority of efficacy endpoint (infarct size at 14 days, WMSI at three months)
- Safety endpoint succeeded: 9/134 treated versus 7/135 control SAEs,  $p < 0.022$
- All three efficacy endpoints failed, all  $p > 0.24$
- Post-hoc analysis showed efficacy in anterior MI subset within 6 hours of MI only, all  $p < 0.04$ , based on 100 patients



# AMIHOT II

- Since the results of AMIHOT I weren't very hot, the sponsors proposed AMIHOT II
- 317 patients from 22 centers, 2.8:1
- Same endpoints as AMIHOT I, anterior MI patients < 6 hours out only
- Safety goal: show  $P(\pi_T < \pi_C + 0.06 \mid \text{data and prior}) > 0.95$
- Hierarchical Bayesian model using all AMIHOT I data



# AMIHOT II

- Hierarchical Bayesian models for safety and efficacy using all AMIHOT I data used four subgroups:
  - Non-anterior MI,  $>6$  Hours (AMIHOT I only)
  - Non-anterior MI,  $\leq 6$  Hours (AMIHOT I only)
  - Anterior MI,  $>6$  Hours (AMIHOT I only)
  - Anterior MI,  $\leq 6$  Hours (AMIHOT I & AMIHOT II)
- Safety model is specified on next slide as an example:



# AMIHOT II Hierarchical Bayesian Model for Safety

- Let  $i = 1, 2$  index study (AIHOT I or II)
- Let  $j = 1, 2, 3, 4$  index subgroup (as above)
- Let  $r$  be a safety-related event,  $C$  be control and  $T$  be treatment
- Population model:

$$r_{ij}^C \sim \text{Binomial}(n_{ij}^C, \pi_{ij}^C)$$

$$r_{ij}^T \sim \text{Binomial}(n_{ij}^T, \pi_{ij}^T)$$

- Parameter model:

$$\lambda_{ij}^C = \text{logit}(\pi_{ij}^C)$$

$$\lambda_{ij}^C = \mu_0 + \omega_j^C + \gamma_i^C$$

$$\pi_{ij}^T = \pi_{ij}^C + \delta_0 + \omega_j^T + \gamma_i^T I(0, 1)$$

# Three Rules From Wise Men



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# Nelson Algren (1909-81)

- Writer
- *The Man With The Golden Arm*
- *A Walk On The Wild Side*
- Simone de Beauvoir's lover!
- 500 page FBI dossier





# Nelson Algren's Three Rules

- Never eat at a place named “Mom’s”



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# Nelson Algren's Three Rules

- Never eat at a place named “Mom’s”
- Never play cards with a man named “Doc”



# Nelson Algren's Three Rules

- Never eat at a place named “Mom’s”
- Never play cards with a man named “Doc”
- Never sleep with somebody who’s got more troubles than you have



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# Walter Cronkite (1916-2009)

- CBS Evening News anchor for 19 years
- “The Most Trusted Man In America”
- Anchored all the moon landings
- If I’ve lost Cronkite, I’ve lost Middle America—Lyndon Johnson



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# Walter Cronkite's Three Rules for Old Men

- Never pass up a free drink



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# Walter Cronkite's Three Rules for Old Men

- Never pass up a free drink
- Never [REDACTED] [REDACTED] [REDACTED]



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# Walter Cronkite's Three Rules for Old Men

- Never pass up a free drink
- Never [REDACTED] [REDACTED]
- Never [REDACTED] [REDACTED] [REDACTED]



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# The End!



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